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IMPACT OF THE HEAT EMISSION SYSTEM ON THE IDENTIFICATION OF GREY-BOX MODELS FOR RESIDENTIAL BUILDINGS

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Abstract

Grey-box modelling is a system identification technique that combines parameter estimation methods to quantify the model parameters and physical knowledge to define the model structure. Consequently, the potential of grey-box modelling lies, in addition to the application of reduced-order models in e.g. control strategies or district simulations, in the characterization of the thermal properties of buildings. Nevertheless, the quality of the obtained model is governed by the dynamic information that is available in the training data. Thereby, the required accuracy of the models, and thus the requirements of the training data, differ from application to application.
This paper analyses how the significant difference in dynamic behavior of a slow floor heating system compared to a highly responsive radiator heating system results in a variation of the time constants of the building that are excited by the system and therefore identifiable in the system identification process. The performance of grey-box models for prediction and simulations are contrasted for cases with radiators and floor heating and the physical interpretability of the model parameters is demonstrated.

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Keywords: grey-box modelling, reduced-order models, control models, system identification

1. Introduction

Building energy simulation (BES) models are widely used to evaluate the energy performance of buildings. Depending on the application and available resources – both on computational and input data level – models with a

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wide range in complexity are found in literature [1]. Whereas state-of-the-art BES-models show good performance in validation studies, the number of model parameters and thus the required input data, increases drastically with the model complexity. As such, the applicability of these models decreases for existing buildings when input-data such as material properties, occupant behavior, etc. are scarce and often uncertain. Moreover, the complexity of the BES-models limits the applicability and scalability for f.i. district energy assessment simulations or control applications were computation time is a limiting factor [2]. As an alternative when measurement data is available, statistic input-output models or black-box models have shown a strong potential [3]. Nevertheless, it is difficult or even impossible to give a physical interpretation to the model parameters. Consequently, these models cannot be used to assess the impact of improvements to the building or the thermal systems.

To overcome this problem, grey-box modeling combines prior physical knowledge about the system to formulate the model structure with statistical data-analysis techniques to estimate unknown model parameters [4]. Assuming that the model structure correctly represents the dynamic behavior, the estimated model parameters can be directly linked to the physical properties of the building. Bacher and Madsen (2011) successfully demonstrate the grey-box modelling framework on measurement data of a 120 m² unoccupied single floor office building subjected to a carefully designed heating experiment [5]. Reynders et al. (2014) use virtual experiments to assess the required availability of measurement data to obtain accurate and robust models for residential buildings. They point out that the model order that is necessary to accurately estimate specific physical properties is higher than for a robust input-output prediction [6]. Therefore one of the main challenges is the identifiability of all model parameters.

In this work, system identification is carried out on virtual experiments to analyze the impact of the heat emission system on the identifiability of grey-box models. A radiator and floor heating system are compared. Thereby, it is expected that due to the strong difference in the way these systems excite the building's thermal mass, significant differences in the optimal model structure and even the identified parameters will be obtained. Section 2, describes the identification process and the suggested reduced-order models. Section 3 presents the detailed building energy simulations focusing on the main simplifications that are expected to have an impact on the identification process. Section 4 shows the results of the model validation process used to identify the appropriate model structure and quantify the accuracy of the identified grey-box models. Finally, the main conclusions are summarized in section 5.

2. Identification of grey-box models

In general, grey-box models consist of a set of continuous stochastic differential equations which define the dynamics of the building, formulated in a state space form that is derived from the physical laws [4]. The unknown parameters ($\boldsymbol{\theta}$) in these equations are derived using maximum likelihood estimation techniques. The model structure is formulated in a state space form, given by equation 1.

$$d\boldsymbol{X}(t) = \boldsymbol{A}(\boldsymbol{\theta})\boldsymbol{X}(t) + \boldsymbol{B}(\boldsymbol{\theta})\boldsymbol{U}(t) + \boldsymbol{\sigma}(\boldsymbol{\theta})d\omega \tag{1}$$

In this equation **X**(t) is the state vector corresponding to the temperatures of different building components. **U**(t) is a vector containing the measured inputs of the system. These inputs can be controllable, such as the heating input or the airflow rate of the ventilation system, or uncontrollable, such as the outdoor climate, internal gains... The model structure, as function of the unknown parameters ($\boldsymbol{\theta}$), is given by the system matrices **A, B, C** and D; $\boldsymbol{\sigma}(\boldsymbol{\theta})d\omega$ introduces the system noise. The measured output of the system **Y**(t) is given in equation 2 as a function of the states **X**(t) and the inputs **U**(t).

$$\boldsymbol{Y}(t) = \boldsymbol{C}(\boldsymbol{\theta})\boldsymbol{X}(t) + \boldsymbol{D}(\boldsymbol{\theta})\boldsymbol{U}(t) + \boldsymbol{\epsilon_t} \tag{2}$$

ϵ_t is the measurement error.

The model structures are derived from resistance-capacitance (RC) networks analogue to electric circuits to describe the thermal dynamics of the systems. Thereby, the distributed thermal mass of the dwelling is lumped to a discrete number of capacitances, depending on the model type. In this work 4 types, ranging from 1st to 4th order models, are investigated in a forward selection procedure whereby the model validation presented in section 4 is used to select the appropriate model structure. Figure 1 shows the RC representation of the implemented 4th order model. The states of the model are linked to the capacities C_i, C_w, C_{wi} and C_f representing respectively the thermal mass of the indoor air, the envelope, the interior walls and the ground floor. Each of these capacities is included because they are linked to different dynamic boundary conditions. Heat transfer through the components is modelled

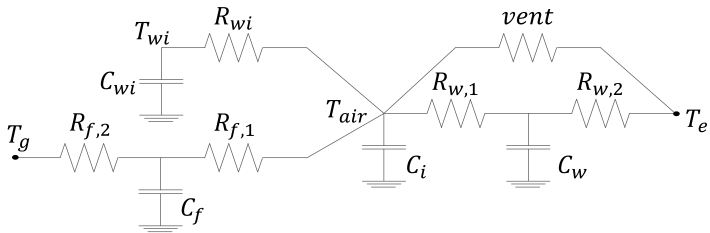

Figure 1 RC representation of the 4th order grey-box model. C_i, C_w, C_{wi} and C_f are respectively the indoor air, external wall, internal wall and floor capacity. T_e and $T_g$are the air and ground temperature used as input for the model. The solar gains and heating input are not show.

by two resistances in series with the thermal capacity of the wall. A parallel resistance is modeled for the ventilation losses. Note that, in the identified models this ventilation term will also include the transmission losses through windows, as their thermal mass is negligible.

The model can be simplified by combining the thermal losses to ground and the outer environment. As such, the 3rd order model is obtained using only C_i, C_w and C_{wi}. The second order model only includes C_i and C_w, making only a distinction between the fast dynamic response of the indoor air and the slower dynamics of the thermal mass of the building structure. Finally, the simplest model is the 1st order model, which only includes C_i. For all model orders the solar gains, internal gains and heating are distributed over the capacities, using weight factors that can be set manually or included in the identification process. Table 1 gives an overview of the different models analyzed in this paper, the way the thermal gains are introduced into these models, and the observation equations that are used in the identification process. For the latter, the impact of using only indoor air temperature as observation in the identification process is compared to a cases where also heat flux measurements are included.

For each of the proposed model structures, the parameters are estimated using the Continuous Time Stochastic Modeling (CTSM) toolbox implemented in R. This process is carried out on 4 different dataset obtained using the models described in section 3. ‘Dat 1’ and ‘Dat 2’ represent two-week data in respectively February (winter) and April (mid-season), while ‘Dat 3’ and ‘Dat 4’ represent 28-day datasets for the same months. A model validation process is carried out to quantify the accuracy of each of the obtained model and identify the most suitable grey-box models. While other tests, such as the analysis of the auto-correlation function of the residuals, time series plots of the 1-step and multi-step predictions, a sensitivity analysis to initial parameter values, etc. were carried out, this paper will demonstrate the differences amongst the identified models by (i) contrasting the root mean squared error (RMSE) for 1-step (15 min), 1-day and 1-week predictions, (ii) cross-validation by simulation on a dataset that differs from the training data and (iii) the physical interpretation of the model parameters.

3. Data obtained by detailed BES-model

Building energy simulations are carried out using a control volume method implemented in the IDEAS-library in Modelica [7] for the heating dominated climate of Uccle (Belgium). The geometry and thermal properties of the dwelling (Table 2) are based on a single family detached dwelling (post ’05) as described in the TABULA building stock description for Belgium [8]. Thereby, a parametric design method is used to come from the aggregated building stock data to a more detailed building model that allows for the assessment of the dominant dynamic phenomena in dwellings. A similar approach was presented in [9] for a two-zone model. In addition to [9], the following simplifications have been introduced:

- the whole building is modelled as a single zone, since the ambition of this paper is merely to demonstrate the difference in identifiability for buildings with floor heating and radiators.
- the floor heating systems is only implemented in the ground floor, not in the internal floor
- the building is unoccupied during the virtual identification experiments. The impact of this assumption and possible solutions to include occupant behavior, such as measurement of electric loads, are proposed in [7]
- all windows are lumped to a single orientation (South). Moreover, the effective solar gains are used as an input for the identification process. The impact of this simplification, as well as alternatives are discussed in [7].

Two different heat emission systems are implemented. Since the emphasis in this work is on the impact of the dynamics of the heat emission system, the model of the heat production unit is simplified to a power-limited ideal

Table 1 Overview analyzed reduced-order models

Model name	Order	Observations	Gain
1 A	1	T_{air}	C_i
2 A	2	T_{air}	C_i
2 B	2	T_{air}	C_w
2 C	2	T_{air}	fitted
3 A	3	T_{air}	C_i
3 B	3	T_{air}	C_w
3 C	3	T_{air}	heating: C_{wi}, solar: fitted
3 D	3	T_{air}, heat flux	fitted
4 A	4	T_{air}, heat flux	fitted
4 B	4	T_{air}, heat flux	heating: C_{wi}, solar: fitted

Table 2 Overview building thermal properties

Parameter	Building D5 (2005-2012)
Area floor	132 m²
Area envelope	390 m²
Volume	741 m³
HLC evelope	253 W/K
HLC floor	67 W/K
C_{air}	4.5 MJ/K
C_{fabric}	121 MJ/K

heating system. This simplification is allowed since the produced heat rather than the gas or electricity consumption is used as an input for the identification process. As such, the need for estimating the often strongly non-linear production and distribution efficiency is avoided.

The radiator is modelled as a thermal capacity which exchanges heat by radiation and convection with the zone, as presented by equation 3 with, C_r and H_r are the thermal capacity and heat transfer coefficients of the radiator and are based on product data, resulting in a thermal capacity of 9.8 kJ/K and a heat transfer coefficient of 350 W/K.

$$\frac{C_r dT_r}{dt} = f_{rad} H_r (T_{star} - T_r) + (1 - f_{rad}) H_r (T_{air} - T_r) + Q_{input} \tag{3}$$

The design fraction of heat that is emitted by radiation (f_{rad}) is 0.3. T_r, T_{star} and T_{air} are respectively the radiator temperature and the star and air temperatures of the zone. Q_{input} is the heat input imposed by a pseudo-random binary sequence (PRBS) as explained below. The floor heating system is modelled as a 1D-model with a prescribed heat flow which is directly imposed to the bottom node of the screed layer in the ground floor. Note that a control volume approach is used to model thermal conduction through the building components. Thereby each material layer is discretized into 5 control volumes. As such, the size of the control volumes varies between 0.4 and 2 cm.

To improve identifiability, the heating system is controlled by a PRBS-signal to assure that the input of the heating system is not correlated to the outdoor climate. The PRBS signal is designed to have a minimum switching frequency of 1 h. Higher frequencies are not included since a 15-minute sampling time is used for the identification and since they would be significantly above the dominant time constants of the building. The input signal for the heating system is obtained by multiplying this PRBS signal with 30% of the nominal power of the heating system, to avoid too high temperatures in midseason and summer. The resulting input is shown further in figure 3.

4. Results

In this section the results of the model validation process are presented. Figure 2 shows the RMSE-values for the identified models. Firstly, a significant decrease for the long-term predictions can be observed for the radiator case (Figure 2 (right)). The RMSE-values indicate that a first-order model in this case is not able to accurately predict the dynamic response of the indoor air. This can be explained by the significant difference between the time constants of the indoor air and the thermal mass which are both directly excited by the radiator heating.

A 2nd order model is able to deal with this problem, significantly reducing the RMSE values. Further increasing the model order to model 3A, results in a strong difference between the 1-day ahead and 1-week ahead predictions, especially for mid-season data (Dat 2 and Dat 4). This indicates that the model is over-parameterized. A problem that can be overcome by including heat flux measurement, as is the case for 3D and 4A. Nevertheless, over-parametrization issues are still shown for the 4th order model, indicating that not enough dynamic information is available in the training data to identify all model parameters. The 3rd order model therefore suffices for this case.

For the floor heating cases (Figure 2 (left)) the decrease in RMSE value for increasing model orders is less significant. Moreover, the level of RMSE-values is in general lower than for the buildings with radiator heating,

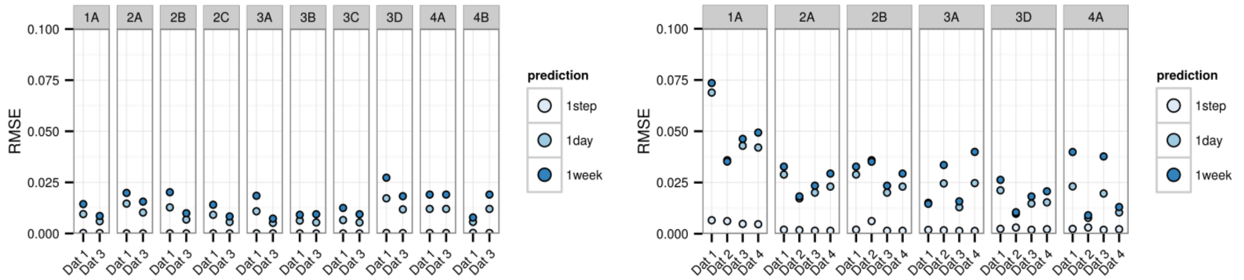

Figure 2 Root mean square error for 1-step, 1-day and 1-week ahead predictions for the floor heating case (left) and radiator cases (right)

even for the 1st order model. This can be explained by the fact that the floor in this case acts as a low-pass filter for the heating system. As such, the high-frequent behavior, that causes the high variations in air temperatures for the radiator system, is suppressed in the case of floor heating. The indoor air and thermal mass of the building react on the same frequencies and can therefore be simplified by a single state model. Note that a correct specification of the observation functions and the distribution of the heat input to the system is of significant importance, as higher RMSE-values are observed for 2B, 3A, 3D and 4A.

Figure 3 shows the indoor air temperature obtained by simulation of the identified models using the cross-validation data. Note that to increase readability, for each order, the models with the highest RMSE-values are not included. Comparison of the temperature profiles for the radiator and floor heating buildings, demonstrates the difference in the dynamic response of the indoor temperature. The block-pulses induced by the PRBS signal are still evident for the radiator system while the floor acts as a low-pass filter in case of floor heating, reducing temperature variations. Nevertheless, the simulation results obtained with the identified models show a better agreement to the data for the radiator cases. Again the inaccurate performance of the 1st order model proves that for radiator heated buildings at least a 2nd order model is required. The 4th order model shows a consistent drift of the indoor air temperature, indicating over-fitting.

For the buildings equipped with floor heating a significant bias is found for models 2A and 3C. This consistent deviation results from the fact that the way the heat input is included in these grey-box models (i.e. to the indoor air) is incorrect for buildings with floor heating. The slight differences between the performance of the 1st order model and the 4th order model, indicate that the former already captures the main dynamic response of the system.

Finally, the model parameters can be physically interpreted. Thereby, Figure 4 shows that for both the radiator and the floor heating models, the estimation of the heat loss coefficient to the outdoor environment (HLCe) is

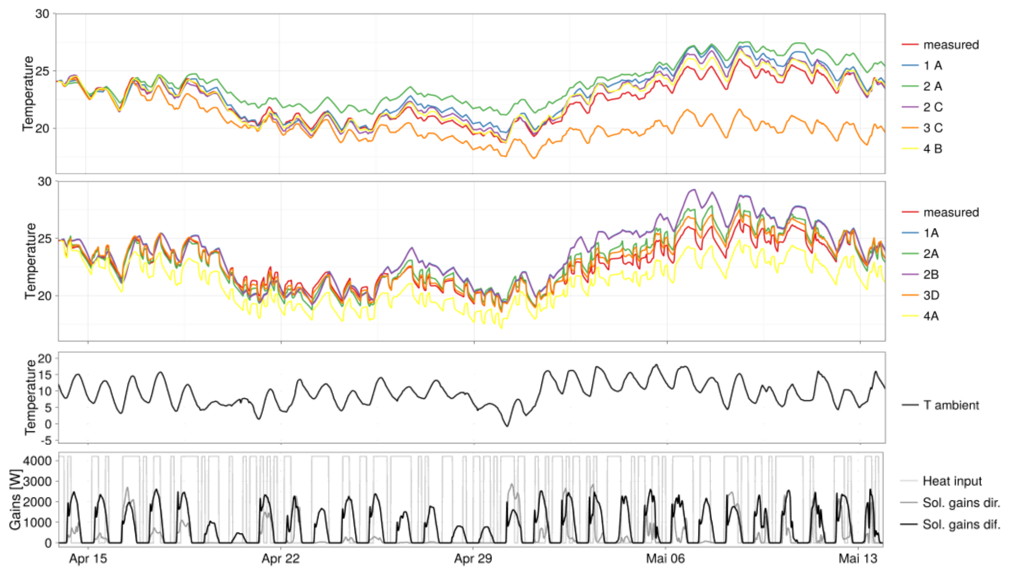

Figure 3 Time series plot of input data (3rd and 4th pane) and cross-validation simulations of the floor heating (1st pane) and radiator heating (2nd pane)

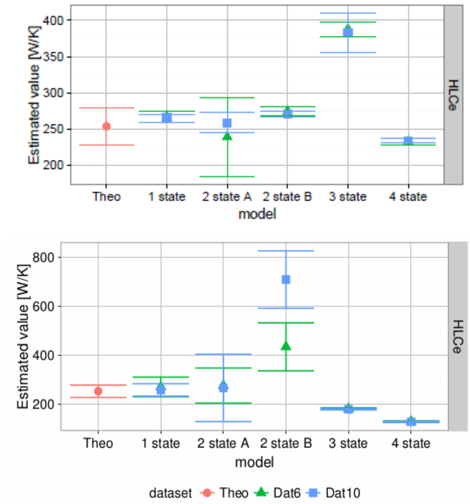

Figure 4 Estimated heat loss coefficients for the floor heating (top) and radiator cases (bottom)

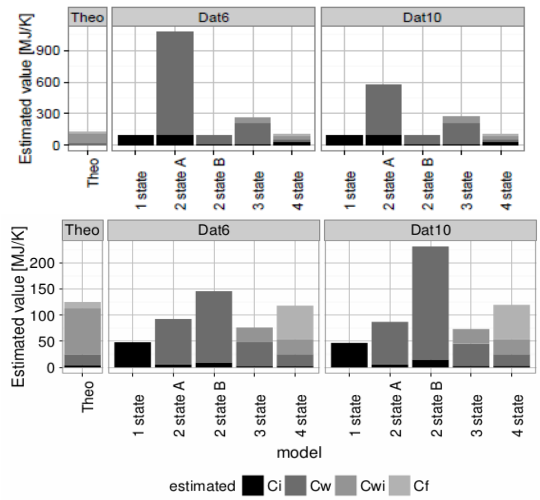

Figure 5 Estimated thermal capacities for the floor heating (top) and radiator (bottom) cases

consistent and has acceptable accuracy, except for scenarios where over-fitting is important. In contrast, heat flux measurements and higher order models are required to get a reliable estimate for the thermal capacities in case of the radiator heating. For the floor heating, the reliability of the estimated thermal capacity strongly depends on the way the heat gains are distributed. It is evident that allocating the floor heating gains to the indoor air is incorrect.

5. Conclusions

In this work the difference in the dynamic excitation of the thermal mass of a dwelling by either floor heating or radiator systems, is shown to have a significant impact on the identifiability and robustness of grey-box models. Firstly, differences in the required model structures are shown. The high-frequent response of the air compared to the structural mass to the radiator heating system, requires at least a 2^{nd} order model. In contrast, due to the low-pass filtering effect of the floor, a single capacity model already gives a good approximation of the dynamic response of a building equipped with floor heating. Secondly, it is shown that not only the lay-out of the RC-network, but also the way that heating and solar gains are introduced have a significant impact on the reliability of the models and the estimated parameters. A good correspondence of the model structure to the actual physics is a prerequisite to give a correct physical interpretation of the estimated parameters.

References

[1] Crawley, D. B., Hand, J. W., Kummert, M., & Griffith, B. T. (2008). Contrasting the capabilities of building energy performance simulation programs. Building and Environment, 43(4), 661–673.
[2] Liu, S., & Henze, G. P. (2006). Experimental analysis of simulated reinforcement learning control for active and passive building thermal storage inventory. *Energy and Buildings*, *38*(2), 142–147.
[3] Kalogirou, S. (2000). Artificial neural networks for the prediction of the energy consumption of a passive solar building. *Energy*,*25*(5), 479-491.
[4] Kristensen, N. R., Madsen, H., & Jørgensen, S. B. (2004). Parameter estimation in stochastic grey-box models. *Automatica*, *40*(2), 225–237.
[5] Bacher, P., & Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*, *43*(7), 1511–1522
[6] Reynders, G., Diriken, J., & Saelens, D. (2014). Quality of grey-box models and identified parameters as function of the accuracy of input and observation signals. *Energy and Buildings*, *82*, 263–274.
[7] Baetens, R., De Coninck, R., Van Roy, J., Verbruggen, B., Driesen, J., Helsen, L., & Saelens, D. (2012). Assessing electrical bottlenecks at feeder level for residential net zero-energy buildings by integrated system simulation. *Applied Energy*, *96*, 74–83.
[8] Cyx, W., Renders, N., Van Holm, M., & Verbeke, S. (2011). *IEE TABULA - Typology Approach for Building Stock Energy Assessment*.
[9] Reynders, G., Diriken, J., & Saelens, D. (2014). Bottom-up modeling of the Belgian residential building stock : influence of model complexity. In SSB 2014 (pp. 1–19).